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DIE STRESS OPTIMIZATION USING QUANTUM BEHAVED PARTICLE SWARM OPTIMIZATION

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ABSTRACT

In metal-forming industries, die is an important tool for fabrication of metal – formed products. Die service life, which is defined as the maximum product number produced by die before it fails, and die performance directly determine the quality of metal-formed product and production cost. In this paper, a methodology for optimization of die stress is developed via the rational design of metal-forming system in such a way that the die stress is optimal. Study proposes a methodology for optimization of die stress via rational design of metal forming process based on three dimensional finite element simulations. For this purpose full factorial experimental design is performed to study the effect of studied factors and their interaction on the die stress. Statistically valid equation is developed and used with quantum behaved particle swarm optimization (QPSO) to determine the optimal values of factors for the minimization of die stress.

KEYWORDS: Die Stress, Finite Element Simulation & Design of Experiment & QPSO

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Original Article

INTRODUCTION

The Forging technology is known for producing parts of superior mechanical properties with minimum waste. In it metals or alloys are plastically deformed to the desired shapes by a compressive force applied with the help of a pair of dies [1]. Die performance and service life decide product quality, time-to-market and production cost. Without suitable die, metal-forming processes are often crippled or rendered totally inefficient [2]. Several tools and approaches have been used such as CAD/CAM, expert system and FEA methods to obtain improvements of die life by proper die design but they rarely include influence of process conditions [3]. Based on this present work concentrates on the study of effect of the process parameters viz. billet temperature, die temperature, friction coefficient and die velocity on the die stress which is a measure of die life. Based on the parametric design approaches the systematic influence of factors and there integrations are considered using three dimensional simulation approach. The approach is statistically validated and finally optimized using quantum behaved particle swarm optimization (QPSO) algorithm [4].

Problem Formulation

For die stress analysis and optimization via rational design of forming system, a part as shown in Figure 1 (a) is used as a case study. In Figure 1 (b) also shows the geometry of punch used to get the deformed product. Material of the Product and Die is specified in Table 1 and Table 2 provides the values of operation parameters considered.

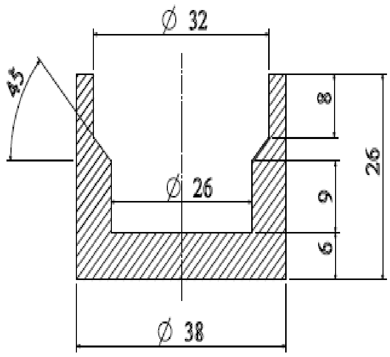

Figure 1(a): Deformed Product

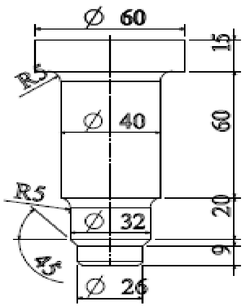

Figure 1(b): Punch Geometry

Table 1: Material Properties

	Billet Material	Die Material
Type	AISI 1043	AISI H13
Temperature (^{0}C)	700-1100	800-1000
Thermal Conductivity (W/m-k)	42.7	28.6
Heat Capacity (J/kg.K)	500	460
Density(10^3 kg/m^3)	7.7-8.03	7.76
Tensile Strength, Ultimate(MPa)	1158	640-2000
Tensile Strength, Yield(MPa)	1034	640-2000

Table 2: Process Parameters and Their Levels

Process Parameters	Symbol	Level 1	Level 2
Billet temp. (^{0}C)	A	1000	1100
Die temperature (^{0}C)	B	250	300
Friction coefficient	C	0.3	0.7
Die velocity (mm/s)	D	0.5	1

METHODOLOGY

To reveal the die stress in the different process parameters, the simultaneous simulation of billet plastic flow and the elastic deformation of die are conducted. Following are the different steps undertaken:

Calculation of Billet Volume

The billet is cylinder and its required dimension is calculated assuming volume constancy of billet and deformed part.

Vol. of Component = 16271.87915 mm^3

Vol. of Billet = Vol. of comp. + Scale loss

Dimension of Billet = 37.6*14.7(mm*mm)

Preparation of CAD Model of the Product

A CAD model of the product is prepared in CATIA using the specification provided in Figure 1. The design is then converted in.STL format so that it can be imported for simulation in DEFORM-3D.

Design of Experiment (DOE)

Design of experiment (DOE) has been a very useful tool to design and analyze complicated industrial design problems. It has been used to systematically determine the optimal process parameters with fewer testing trials and to find out what happens to the output or response when the settings of the input variables in a system are purposely changed.

In many scientific Investigations the interest lies in the study of effects of two or more factors simultaneously. Factorial designs are most commonly used for this type of investigation. Here we consider the important class of factorial designs for k factors each at two levels. Because this class of designs requires 2 x 2 x … x 2 = 2^k observations, it is referred to as 2^k factorial designs. It is also called the class of 2^k full factorial designs. Since each factor only has two levels, they are used to study the linear effect of the response over the range of the factor levels chosen. Factorial effects, which include main effects and interaction effects of different order, are defined. Estimation and testing of factorial effects for location and dispersion models are considered for replicated and un-replicated experiments [5]. An experiment was created and it employed full factorial arrangements, that is, the design comprised all possible combinations of factors considering different levels. The process parameters are selected and examined, each at two levels. The different combinations are shown below in Table 3.

Table 3: Experimental Set up

Exp. No.	A	B	C	D
1	1000	250	0.3	0.5
2	1100	250	0.3	0.5
3	1000	300	0.3	0.5
4	1100	300	0.3	0.5
5	1000	250	0.7	0.5
6	1100	250	0.7	0.5
7	1000	300	0.7	0.5
8	1100	300	0.7	0.5
9	1000	250	0.3	1
10	1100	250	0.3	1
11	1000	300	0.3	1
12	1100	300	0.3	1
13	1000	250	0.7	1
14	1100	250	0.7	1
15	1000	300	0.7	1
16	1100	300	0.7	1

On the basis of above experimental set up, total 16 experiments have been conducted by the use of computer simulation technique using Deform 3D software.

Simulation

Here Simulation has been carried out for various design scenario discussed above. For simulation we used

DEFORM-3D software. Following are the simulation properties used as given in Table 4.

Table 4: Operation Parameters Assigned to Complete the Simulation

Forging Equipment	Punch Die
Number of elements	45000
Mesh type	Tetrahedral
Die displacement	0.5 mm
Simulation mode	Isothermal
Simulation step	50
Step increment	2
Primary die	Top die
Environment Temperature	20^0C

After conducting all the simulation, the different effective stress has been noted for further analysis and optimization.

Analysis of Experiments

Analysis of the experimental data obtained from full factorial design is done on MINITAB R14 software using full quadratic re- sponse surface model as given by eq. (i).

$$y = b_0 + \sum_{i=1}^{k} b_i x_i + \sum_{i=1}^{k} b_{ii} + \sum_{kj} \sum b_{ij} x_i x_j \quad \text{(i)}$$

Where y is the response, x_i is i^{th} factor, k is total number of factors.

The t-test was performed to determine the individual significant term at 95% of confidence level and final response surface equations for the input parameters and the output. To check the feasibility of the experimental value the residuals of each trial are computed. The probability plot of residuals is plotted keeping the 95% confidence level for the fitted distribution.

Optimization

An optimization consists of maximizing or minimizing a real function by systematically choosing input values from within an allowed set and computing the value of the function. More generally, optimization includes finding "best available" values of some objective function given a defined domain, including a variety of different types of objective functions and different types of domains**.**

Based on the analysis made, the most significant factors on Die stress are evaluated. The optimized parameter levels that can be established for minimum Die Stress is found using QPSO technique.

In the quantum model of a PSO called here QPSO, the state of a particle is depicted by wave function ψ(x; t), instead of position and velocity. The dynamic behaviour of the particle is widely divergent form that of that the particle in classical PSO systems in that the exact values of xi and vi cannot be determined simultaneously. In this context, the probability of the particle’s appearing in position xi from probability density function v(x; t) [6].

Employing the Monte Carlo method, the particles move according to the following iterative eq. (ii) and (iii).

$$X_i\,(t+1) = p + b \times [Mbest - X_i\,(t)] \times 1n\,(1/u), \text{ if } k \geq 0.5 \quad \text{(ii)}$$

$$X_i\,(t+1) = p - b \times [Mbest - X_i\,(t)] \times 1n\,(1/u), \text{ if } k < 0.5 \quad \text{(iii)}$$

Where **b** is a design parameter called contraction–expansion coefficient, **u** and **k** are values generated using the uniform probability distribution functions in the range [0,1].

The global point called Mainstream Thought or Mean Best (*Mbest*) of the population is defined as the mean of the *Pbest* positions of all particles and it given by eq. (iv).

$$\text{Mbest} = 1/n \sum_{d=1}^{n} p_{g,d}(t) \tag{iv}$$

where g represents the index of the best particle among all the particles in the swarm. In this case, the local attractor to guarantee convergence of the PSO presents the following coordinates given by eq. v.

$$P = (C_1P_{i,d}+C_2P_{g,d})/(C_1+C_2) \tag{v}$$

Following Are Its Steps

Step1: Initialization of swarm positions: Initialize a population (array) of particles with random positions in the n-dimensional problem space using a uniform probability distribution function.

Step2: Evaluation of particle's fitness: Evaluate the fitness value of each particle. We are minimizing, rather than maximizing, the fitness function in this paper.

Step3: Updating of global point: Calculate the ***Mbest***

Step4: Comparison to ***pbest*** (personal best): Compare each particle's fitness with the particle's ***pbest***. If the current value is better than ***pbest***, then set the ***pbest*** value equal to the current value and the pbest location equal to the current location in the n-dimensional space.

Step5: Comparison to ***gbest*** (global best): Compare the fitness with the population's overall previous best. If the current value is better than gbest, then reset gbest to the current particle's array index and value.

Step6: Updating of particles' position: Change the position of the particles where c1 and c2 are two random numbers generated using a uniform probability distribution in the range [0,1].

Step7: Repeating the evolutionary cycle: Loop to Step 2 until a stop criterion is met, usually a sufficiently good fitness or a maximum number of iterations (generations). After utilizing all the steps we find the optimized value of die stress and the factors.

RESULTS

After setting all the parameters in DEFORM pre-processor all 16 simulations are run. The initial Positioning of Dies are shown in Figure 2. Different views of deformed product are shown in Figure 3 and Figure 4. The result of all simulation has been shown in Table 6.

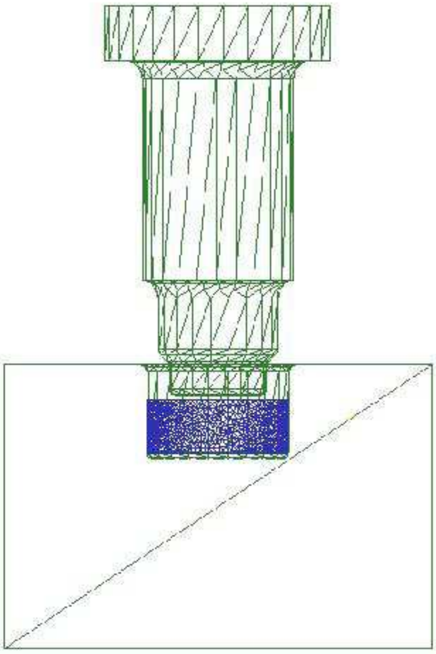

Figure 2: Initial Positioning of Dies

Figure 3: Solid View of Deformed Product

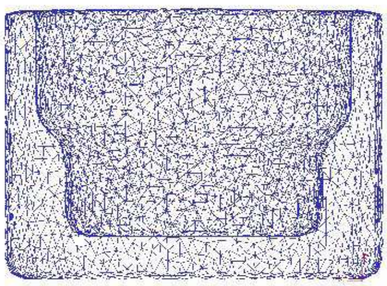

Figure 4: Meshed View of Deformed Product

Table 5: Simulation Results of Die Stress

Exp. No.	A (^{0}C)	B (^{0}C)	C	D (mm/s)	Die Stress (MPa)
1	1000	250	0.3	0.5	557
2	1100	250	0.3	0.5	467
3	1000	300	0.3	0.5	544
4	1100	300	0.3	0.5	482
5	1000	250	0.7	0.5	835

Table 5: Contd.,					
6	1100	250	0.7	0.5	548
7	1000	300	0.7	0.5	798
8	1100	300	0.7	0.5	566
9	1000	250	0.3	1	523
10	1100	250	0.3	1	476
11	1000	300	0.3	1	625
12	1100	300	0.3	1	473
13	1000	250	0.7	1	773
14	1100	250	0.7	1	439
15	1000	300	0.7	1	835
16	1100	300	0.7	1	546

Analysis of Results

Relative influence of each factor is determined by analysis of variance method (ANOVA) and results are presented in Table 7. ANOVA results show that both main effect and interaction are important.

Table 6: Analysis of Variance for Die Stress

Source	D.O.F	SS	Variance	F- Value	P- Value
Main Effects	4	273472	68367.9	534.28	0.000
2- Way Interactions	6	44790	7465.0	58.34	0.000
Residual Error	5	640	128.0		
Total	**15**	**318901**			
D.O.F. = Degree of Freedom; SS = Sum of Squares					

Final equation is given as

Stress = *586.69-99.56A+21.94B+80.81C-12.94D+7.69AB-43.19AC-15.69AD-3.19BC+24.06BD-6.31CD* (vi)

Terms in the above equation explain the total variation of 99.80%. The error between the values predicted using developed equation and experimental values shows the normal distribution as in Figure 5.

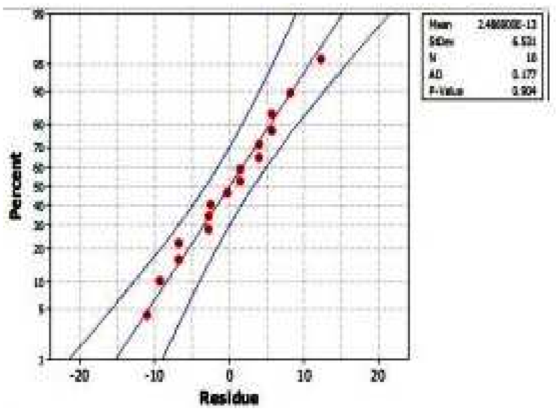

Figure 5: Probability Plot of Residue

These results explain that develop model is valid and can be used for optimum value determination. Half normal probability plot is employed to graphically predict the significant factors and terms and results are shown in Figure 6.

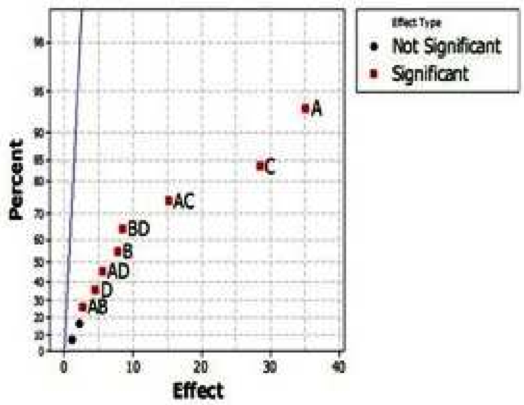

Figure 6: Half Normal Plot At 95% of Confidence Level

Optimization

For optimization purpose QPSO is used with population size of 50 and total number of iteration as 500. The result of QPSO is depicted in Figure 7.

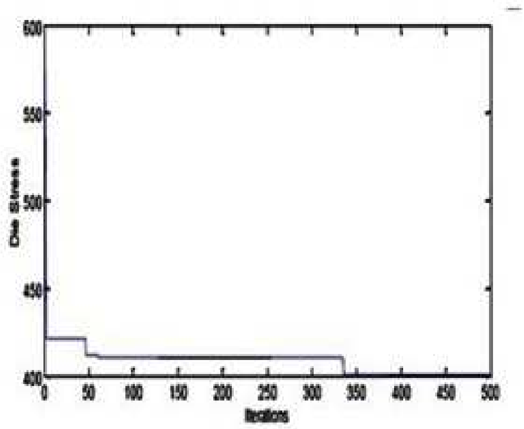

Figure 7: Convergence Curve for QPSO

The minimum die stress value found is **400.57 MPa**. The process parameters at this value are given in Table 8.

Table 7: Optimum Process Parameter Values

Process Parameter	Value
Billet temp.(^{0}C) (A)	1099.51
Die temp.(^{0}C) (B)	252.6375
Friction co. (C)	0.3367
Die vel.(mm/s) (D)	0.904425

CONFIRMATION SIMULATION

Setting all the optimized parameters we get by optimization is set in DEFORM pre-processor and simulation is being run. Die Stress distribution at this value shows that the optimization is achieved Die Stress Distribution is shown in Figure 8.

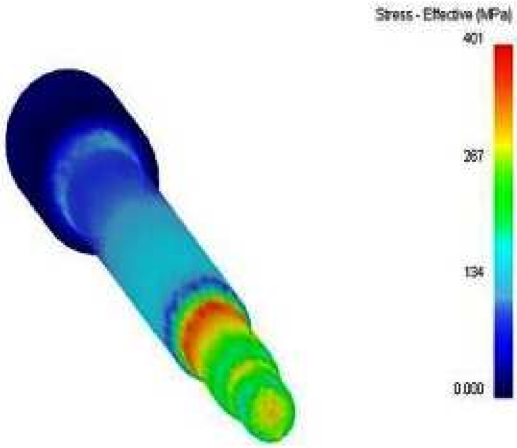

Figure 8: Stress Distribution in the Die

CONCLUSIONS

- The Process parameters taken here are found to be significant in Die Stress.
- The interaction of process parameters are also found significant in Die Stress.
- A statistical relation is found using factorial method between the input parameters and the output Die Stress.
- The relation is statistically validated as the residual is found to be uniformly distributed.
- The optimum die stress and process parameters are found using QPSO.
- Simulation trial using optimum process parameters gives min. die stress of 401 MPa which is nearly equal to the optimized die stress found using QPSO.

The use of Factorial method and QPSO to optimize the die stress is found to be an effective tool as it saves time and effort both.

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